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Abstract

This study provides insight into how CMIP5 climate models perform in simulating summer and winter precipitation, at different geographical locations and climate conditions. Precipitation biases in the CMIP5 historical (1901-2005) simulations relative to the Climatic Research Unit (CRU) observations are evaluated over 8 regions exhibiting distinct seasonal hydroclimates: moist tropical (Amazonia and central Africa); monsoonal (southern China); moist continental (central Europe); semi-arid (western United States and eastern Australia); and polar (Siberia and Canada). While the bias and monthly quantile bias (MQB, defined herein) reflect no substantial differences in CMIP5 summer and winter precipitation simulations at the global scale, strong seasonality and high inter-model variability are found over the selected moist tropical regions (i.e., Amazon and central Africa). In the semi-arid regions, high inter-model precipitation variability is also displayed, especially in summer, while the median of simulations is an overestimate of both winter and summer precipitation. In Siberia and central Europe, most CMIP5 models underestimate summer precipitation, and overestimate it in winter. Also, the MQB values decrease as the choice of quantile thresholds increase, implying that the underestimation of summer precipitation is primarily associated with biases in lower quantiles of the precipitation distribution. While the CMIP5 models exhibit similar behaviors in simulating high-latitude winter precipitation, they differ substantially in summer simulations for the selected Canadian and Siberian regions. Finally, in the monsoonal southern China region, CMIP5 models exhibit large overall precipitation biases in both summer and winter, as well as at higher quantiles.

keywords: Precipitation; Climate; CMIP5

1 Introduction

Global climate models have been used to simulate historical and projected precipitation for climate change and variability studies. Several modeling groups and international collaborative activities, such as the Intergovernmental Panel on Climate Change (IPCC; IPCC (2007)), provide data sets of historical and future climate simulations. However, climate model simulations are subject to uncertainties and biases because of errors in model parameterization, boundary conditions, simplifying assumptions, model structure, and input variables (Feddema et al. (2005); Tebaldi et al. (2006); John and Soden (2007); Reichler and Kim (2008); Liepert and Previdi (2012)).

Water resources are particularly sensitive to changes in precipitation, which is a key variable in understanding the global water cycle and analyzing water availability (Seager et al. (2007); Kharin et al. (2007); Madani and Lund (2010); Cayan et al. (2010); Sivakumar (2011); Stoll et al. (2011); Azarderakhsh et al. (2011); Wehner (2012); Hassanzadeh et al. (2013); AghaKouchak et al. (2013); Nazemi et al. (2013); Mirchi et al. (2013)). However, GCM-based precipitation simulations are inherently uncertain and subject to systematic and unpredictable (random) biases (Feddema et al. (2005); Min et al. (2007); Brekke and Barsugli (2013); Mehrotra and Sharma (2012)). Therefore, quantification and characterization of biases and uncertainties in GCM-based precipitation climate simulations are necessary for understanding the available data sets and their potential applications in water cycle analysis and future water resources management.

Recently, the Coupled Model Intercomparison Project Phase 5 (CMIP5) has provided the climate community with a suite of coordinated climate model simulations to facilitate addressing science and policy questions relevant to the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report (AR5) (Meehl and Bony

(2011); Taylor et al. (2012)). Compared to the Phase 3 of the project (CMIP3), which contributed to the IPCC 4th Assessment Report, the CMIP5 simulations incorporate more advanced treatments of land use change and anthropogenic aerosols forcings (Knutti (2010); Taylor et al. (2012); Stott et al. (2013);). By considering multiple climate models with different model physics and/or forcings, the CMIP5 experiment provides an *ensemble of opportunity* to explore uncertainty in climate model simulations (Stott et al. (2013)).

Given the uncertainties in forcings, initial conditions, and model structures, one cannot expect climate models to accurately replicate historical observations in every respect. Since the development of the first climate models, evaluation of historical climate simulations against ground-based observations has become an ongoing activity of the climate community (Bony et al. (2006)), since future improvements in climate model simulations largely rely on extensive and targeted evaluation studies. Gleckler et al. (2008) has introduced a number of performance metrics for evaluation of climate model simulations against observations. AghaKouchak and Mehran (2013) also has proposed several volumetric indicators and skill scores for assessing biases in climate model simulations.

A myriad of studies have focused on validation of climate model historical precipitation simulations (e.g., Phillips and Gleckler (2006); Dai (2006); Sun et al. (2007); Chen and Knutson (2008); Schaller et al. (2011); Moise and Delage (2011); Liu et al. (2012); Flaounas et al. (2012); Watanabe et al. (2012); Schubert and Lim (2013); Kharin et al. (2013); Sillmann et al. (2013); Hirota and Takayabu (2013); Gaetani and Mohino (2013); Kumar et al. (2013); Catto et al. (2013); Knutti and Sedláček (2013); Balan Sarojini et al. (2012); Deser et al. (2012)). In a recent study, Mehran et al. (2014) evaluated a wide range of CMIP5 historical precipitation simulations and concluded that over many regions most CMIP5 precipitation simulations were in fairly good agreement with satellite observations. However, over deserts and certain high latitude regions, there were major discrepancies between model simulations and observations. Mehran et al. (2014) also showed that while removing the mean-field bias improves the overall bias, it does not lead to a significant improvement at higher quantiles of precipitation simulations. Hao and AghaKouchak (2013) evaluated changes in joint precipitation and temperature extremes in CMIP5 simulations against ground-based observations. Their results showed that models simulations agreed with ground-based observations on the sign of the change in occurrence of joint extremes; however, discrepancies were observed on regional patterns and magnitudes of change in individual CMIP5 climate models.

The present study evaluates the seasonal and regional biases in CMIP5 historical (1901-2005) simulations of continental precipitation with respect to the observational Climatic Research Unit (CRU; Mitchell and Jones (2005)) data set, using several quantitative statistical measures. Furthermore, the cumulative distribution functions (CDFs) of the CMIP5 precipitation simulations are investigated, especially at higher quantiles of precipitation. The seasonal (summer and winter) biases are evaluated against observations over 8 regions across the globe. The selected regions have distinct climate and seasonality, and hence the study provides insight into how models perform at different geographical locations and climate conditions. The remainder of the paper is organized as follows. The reference data and climate model simulations are briefly introduced in Section 2. In Section 3, the methodology and results are discussed in detail. Section 4 is devoted to concluding remarks.

2 Data

The Climatic Research Unit (CRU, New et al. (2000); Mitchell and Jones (2005)) monthly precipitation data are used as reference observations. CRU data sets have been widely applied in many regional and global studies, and have been validated against other observational data sets (precipitation, Tanarhte et al. (2012); temperature, Morice et al. (2012); Jones et al. (2012)). In this study, 34 CMIP5 precipitation simulations and their multimodel ensemble median for the period 1901-2005 are evaluated relative to CRU observations. Table 1 lists the CMIP5 model simulations considered in this study. In addition to simulations by physical climate models that include prescribed historical atmospheric CO_2 concentrations, runs of "Earth Systems Models" with a prognostic global carbon cycle that are driven by the corresponding prescribed historical CO_2 emissions (designated by the suffix _esm) also are considered here. The CMIP5 simulations are archived in the Global Organization for Earth System Science Portals (GO-ESSP) coordinated by the United States Department of Energy (DOE) Program for Climate Model Diagnosis and Intercomparison (PCMDI). For consistency, the CMIP5 precipitation simulations and CRU observations are all re-gridded to a common 2^o x 2^o spatial resolution.

3 Methodology

In this study, summer is defined as June, July, and August (JJA) in the Northern Hemisphere (NH) and December, January, and February (DJF) in the Southern Hemisphere (SH), whereas winter is defined as DJF in the NH and JJA in the SH. First, summer and winter biases in CMIP5 climate model simulations are estimated for the entire distribution of precipitation ($B = \Sigma_{i=1}^{n}\left(SIM_i\right)/\Sigma_{i=1}^{n}\left(OBS_i\right)$, where SIM and OBS denote simulations and observations, while $i = 1, \ldots, n$ refer to a particular sample of the observations and corresponding simulations). Then, the monthly quantile bias (MQB; AghaKouchak et al. (2011)) is derived for a number of areas around the globe, in order to further study the corresponding regional summer and winter biases. The MQB is defined as the mean ratio of CMIP5 simulations (hereafter, SIM) over CRU observations (hereafter, OBS) above the quantile q:

$$MQB = \frac{\Sigma_{i=1}^{n} \left(SIM_i | SIM_i \geq q \right)}{\Sigma_{i=1}^{n} \left(OBS_i | OBS_i \geq q \right)} \tag{1}$$

An MQB of 1 corresponds to no bias in model simulations versus ground-based observations above the choice of quantile threshold (e.g., the 75th or 90th percentiles of non-zero precipitation data for each model separately). Note that in all models, small values below the typical precipitation detection limits (here, $10^{-}5$mm/s or $\approx$ 0.9mm/day) are assumed to be zero. The MQB values are computed for selected regions in the western United States, Australia, Amazon, Europe, Canada, Siberia, southern China, and central Africa (see Figure 1) for summer and winter. The selected boxes cover regions with different climatic conditions. The regional climates can be broadly described as: *moist tropical* (Amazonia and central Africa); *monsoonal* (southern China); *moist continental* (central Europe); *semi-arid* (western United States and eastern Australia); and *polar* (Siberia and Canada).

The designations of regional climates follow a hydroclimatic schema: *moist tropical* implies that summer and winter rainfall is associated with shifts in the convective Intertropical Convergence Zone (ITCZ); *monsoonal* regions occur where the prevailing seasonal winds produce a wet summer but a relatively dry winter; *moist continental* describes regions having both moist summers and winters; *semi-arid* suggests generally drier seasons, especially in summer; and *polar* regions are associated with cold, snowy winters and cool, moist summers. In the selected regions, only simulations over land are evaluated where ground-based observations are available.

4 Results

Figure 2 displays the bias ratios of 12 selected CMIP5 simulations in summer, whereas Figure 3 shows winter bias ratios for the same models (white areas in the panels correspond to no data in simulations or observations). One can see that several models show distinct differences (often opposite sign of bias) in summer and winter. For example, most models underestimate summer precipitation in Europe, while they overestimate winter precipitation. Over Amazonia, on the other hand, most models overestimate summer precipitation, while they underestimate winter precipitation. In several parts of the globe, including the western U.S., most models tend to overestimate precipitation in both summer and winter. Figure 4 displays the global averages of the overall bias, MQB above 75th quantile (Q75), and MQB above 90th quantile (Q90) for all 34 CMIP5 models as well as their ensemble median. All panels in Figure 4 show a consistent positive bias, in that none of the climate models global averages underestimate precipitation relative to observations. With respect to global averages, all CMIP5 climate models and their ensemble median overestimate precipitation in summer and winter by between about 2% to 33%. As shown, the bias and MQB values of summer and winter global averages are similar, though overall, the bias and MQB values in summer are slightly higher than those of winter.

Unlike global averages of summer and winter, the regional summer and winter biases over the selected geographical and climatic regions are substantially different. Figure 5 displays the regional summer and winter biases for all the CMIP5 models and their ensemble median over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, and (h) south China. Figures 6 and

7 show similar figures for MQB Q75 (75th percentile threshold) and MQB Q90 (90th percentile threshold), respectively.

One can see that most models and their ensemble median underestimate summer precipitation over Europe, while they overestimate winter precipitation there (Figure 5a) - see also Scoccimarro et al. (2013). As shown, model biases are less (closer to 1) at higher quantiles (Figures 6a and 7a), suggesting that the overall summer and winter biases are associated more with lower quantiles of precipitation. This result can be understood as a general tendency for today's climate models to simulate light rainfall too frequently, and intense rainfall too rarely (Sillmann et al. (2013)). Such an excessive "drizzle" phenomenon, presumably associated with unrealistic representation of the microphysics of precipitation, was previously noted as a common error in earlier-generation models (Dai (2006); Sun et al. (2007); Stephens et al. (2010)). This error apparently carries over to the CMIP5 models as well, but will be shown to vary with region in the analysis that follows.

In contrast to central Europe, most CMIP5 model simulations underestimate winter precipitation over the Amazon region (see Figure 5b). The overall bias (Figure 5b) and MQB values (Figures 6b and 7b) for the CMIP5 models, as well as for their ensemble median, indicate that CMIP5 climate models simulate precipitation here somewhat more reliably in summer than in winter. It should be noted that winter MQB values also are higher than those of summer (e.g., compare MQB above Q90 in summer and winter in Figure 7b).

The regional bias and MQB over central Africa are plotted in Figures 5c, 6c, and 7c. As shown, the CMIP5 inter-model variability with respect to bias is substantial in both summer and winter precipitation simulations. The overall bias values are somewhat higher in summer, while the MQB values are higher in winter, indicating that there are substantial biases associated with high quantiles of winter precipitation simulations in central Africa. On the other hand, the overall summer biases can be attributed more to light rainfall events, as the overall biases are larger than corresponding MQB values.

Amazonia and central Africa both can be categorized as moist tropical regions in which summer or winter rainfall is associated with shifts in the convective Intertropical Convergence Zone (ITCZ; Waliser and Gautier (1993)). In SH summer (DJF) the ITCZ, a narrow band of intense convective rainfall, moves south of the Equator, and both Amazonia and central Africa receive heavier convective precipitation than in SH winter (JJA). In both regions, the inter-model variability of precipitation is high, which is probably associated with the varying ability of the models to correctly simulate the ITCZ precipitation. It is well-known that climate models' precipitation errors tend to be large in tropical regions such as Amazonia and central Africa, where shortcomings in model representations of convection are most apparent (Randall et al. (2007)). For this reason, numerous studies have focused on improving sub-grid scale parameterizations of convective events.

Figures 5d, 6d, and 7d display the CMIP5 models' overall summer and winter biases B and MQB values for semi-arid eastern Australia. In both seasons, most models overestimate precipitation, but since the summer biases deviate more from the optimum value of 1 ($B = 1$ indicates "no bias"), it can be concluded that the models display somewhat better skill in simulating winter precipitation. A possible physical explanation for this seasonal asymmetry is that convective precipitation, which is prevalent in summer, is more poorly simulated than winter frontal precipitation, which is more realistically represented in today's climate models (e.g. Catto et al. (2010)). The inter-model variability of the biases is also more substantial in summer than winter: although several CMIP5 models substantially underestimate Australian summer precipitation, a few models overestimate it by more than 180% , yielding an overall ensemble-median overestimation of summer precipitation. The MQB values are of similar magnitude for summer and winter, however, suggesting that the larger overall biases in summer are attributable to errors in simulating lighter rainfall events over eastern Australia.

Figures 5e, 6e, and 7e present the overall bias and MQB values for the CMIP5 models and their ensemble median over another semi-arid region, the western United States. Here almost every CMIP5 model is seen to overestimate both summer and winter precipitation, characteristics that are displayed by the corresponding ensemble medians as well (with precipitation overestimated by about 31% and 37%, respectively). As their MQB values demonstrate, the CMIP5 models also substantially overestimate precipitation at high quantiles in both seasons. It is noteworthy that the winter biases, in particular, display somewhat more inter-model variability than in eastern Australia (Figures 5d, 6d, and 7d), possibly because of the more important role played by topography in determining the climate of the western U.S. In this respect also, there are inter-model variations in the placement of the high/low biases (B>1 / B<1) in the western United States (see Figure 3). Few of the models display high precipitation biases over the steep but spatially narrow Sierra Nevada mountain chain of California, for example, while most models exhibit a high bias over the broader Rocky mountain cordillera near the center of the western U.S. region defined in Figure 1. These spatial variations in precipitation bias are mainly a consequence of the relatively coarse horizontal resolution of the typical CMIP5 model (a 2x2 degrees latitude/longitude grid) which effectively smooths and flattens topography, thereby distorting its impact on precipitation. Hence, increased horizontal resolution and improvements in the dynamics of atmospheric flow over topography in climate models could substantially improve their simulation of precipitation (Wehner et al. (2010); Ghan et al. (2002)).

The overall bias and MQB values for the CMIP5 models and for their ensemble median over the polar Siberian region are displayed in Figures 5f, 6f, and 7f. It can be seen that the inter-model variability of simulated summer precipitation biases are much higher than in the winter simulations, but the ensemble median result is very close to the CRU observations in this region. The winter simulations generally over-predict the observations, but by relatively small amounts. In contrast to the semi-arid western U.S., the MQB of precipitation simulations over Siberia are less than the corresponding B values, indicating that lower quantiles of precipitation contribute more to the overall bias. The Siberian simulations thus exemplify the common problem of excessive light and mid-range precipitation, but they display this tendency more in summer when frontal systems (i.e. extratropical cyclones) are weaker, and when convective processes contribute a greater fraction of the total precipitation.

In contrast to their Siberian precipitation simulations, CMIP5 models and their ensemble median generally overestimate summer precipitation in the alternative polar region of northern Canada (see Figure 5g). The overall bias and MQB values for summer precipitation simulations also are substantially greater than those in Siberia (compare Figures 6g, and 7g with Figures 6f, and 7f), indicating more problematical simulation of heavy precipitation. Here, topography (e.g. the Canadian Rocky Mountain chain) may be partly responsible for some of the differences in summer biases with respect to Siberia. In winter, however, the overall biases and MQB values for Canada and Siberia are quite similar, suggesting a generally satisfactory CMIP5 simulation of the frontal systems that predominate in these polar regions.

In the monsoonal southern China region, the CMIP5 models and their ensemble median clearly overestimate precipitation in both summer and winter (Figures 5h, 6h, and 7h). Unlike, most other selected regions, the overall summer and winter precipitation biases are also reflected consistently at high quantiles of precipitation, indicating a general overestimation of intense precipitation events, but also with a fairly high degree of inter-model variability. In summer, southern China is subject to monsoonal convective systems, but in winter, more to frontal systems with generally drier "background" conditions. Limitations of climate models in capturing monsoonal and convective events have been recognized in previous publications (e.g., IPCC (2007) Ch. 8), but the general overestimation of winter precipitation implies that the CMIP5 simulations of frontal systems and/or the parameterization of microphysical processes may also be problematical in this region.

The study results indicate that the biases of CMIP5 simulated summer and winter precipitation are qualitatively different across regions. Figures 8 and 9 provide further insights into the distinct differences in the empirical cumulative distribution functions (CDFs) of the observed (black lines) and CMIP5 simulations (green lines) in summer and winter, respectively. (In these figures, green simulation lines situated rightward/below the observations (black line) imply the overestimation of precipitation, and vice versa.) For example, it is seen that the lower quantiles of simulated precipitation are generally underestimated relative to CRU observations in central Europe and Amazonia, but they are overestimated in the western United States and Siberia.

Figures 8 and 9 also highlight structural differences in the regional CDFs , providing insights into how the midrange values (near F(x) = 0.5) of the CMIP5 simulations vary across different regions. For example, the CDFs of the summer precipitation in the selected moist tropical regions are inflected in this midrange, possibly indicating marked differences in the physical processes that are operative in lighter versus heavier precipitation events. In polar regions, it is also apparent that the midrange values of summer precipitation are overestimated in CMIP5 simulations relative to CRU observations.

To show the variability and robustness of the biases across the models and regions, boxplots of biases values in summer and winter are presented in Figures 10 and 11. The figures display the median (red lines), 25th and 75th percentiles edges, and whiskers of simulated precipitation biases for each model and region separately (whiskers represent variability outside the upper (here, 75th) and lower (here, 25th) percentiles). One can see that there is substantial variability, not only model-to-model, but also region-to-region. In these figures, where the ensemble median stands relative to the intermodel range also indicates how consistent the simulation biases are across the selected CMIP5 models.

It is acknowledged that observational (here, CRU) data are subject to uncertainties, especially in the first half of the 20th century, when the spatial coverage of available observations was quite limited (Ferguson and Villarini (2012); New et al. (2000)). To assess the robustness of the results, the analyses presented in this paper have been tested for the more reliable observations from the period 1951-2005. The results are provided as Supplementary Material (see Figures S1 to S6), corresponding to Figures 4 to 7. As shown, the results do not change substantially when data from the first half of the 20th century are eliminated from the analysis. To further examine the robustness of the statistics, the same analyses are performed using the University of Delaware precipitation data (Nickl et al. (2010)). As an example, Figure S7 (Supplementary Material) displays the global averages of the overall bias, MQB above 75th quantile (Q75), and MQB above 90th quantile (Q90) for all the CMIP5 models and their ensemble median relative to the University of Delaware (UD) global precipitation data (Similar to Figure 4, but with the UD precipitation as reference observation). One can see that the global average statistics are very similar using both CRU and UD observations. Figure S8 (Supplementary Material) shows the Regional summer and winter relative to the UD precipitation data over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, (h) south China (Similar to Figure 5, but with the UD precipitation as reference observation).

One can see that even at the regional scale, the presented statistics using two different observational data sets are consistent.

5 Concluding Remarks

Recent advances in numerical computing and climate models have led to an increase in climate simulations of the past and future. However, climate model simulations are inherently subject to many uncertainties, and thus diverse methods are needed to comprehensively quantify simulation biases and the physical errors associated with them. The United States Global Change Research Program (USGCRP (2009)) identifies areas in which uncertainties limit our ability to estimate future climate change and its regional impacts that will entail mitigation and adaptation policy decisions. The quantification of biases in climate model simulations is therefore a prerequisite for future advances in both model development and policy formulation.

In this paper, the seasonal and regional biases in CMIP5 historical (1901-2005) simulations are evaluated against the Climatic Research Unit (CRU) ground-based observations. The selected regions exemplify moist tropical, monsoonal, moist continental, semi-arid, and polar hydroclimatic regimes. The cumulative distribution functions (CDFs) of the CMIP5 precipitation simulations also are investigated, especially at higher quantiles (i.e., 75th and 90th percentiles) that are relevant to the analysis of heavy precipitation events (Benestad (2003); Benestad (2006)).

The global averages of overall bias (B) and monthly quantile bias (MQB) values indicate no substantial difference in summer versus winter precipitation simulations. In fact, at a global scale, all models overestimate the total precipitation amount as well as its higher quantiles (e.g., 75th and 90th percentiles). However, strong seasonality in bias values is observed over the selected moist tropical regions (Amazonia and central

Africa). Furthermore, the models exhibit high inter-model variability in the selected tropical regions, particularly in winter precipitation simulations. In both regions, substantial biases are observed at high quantiles of precipitation. Moreover, the CDFs of the summer precipitation in the selected Amazonian and central African tropical regions (in contrast those of other regions) are more inflected in their midrange, possibly reflecting marked differences in the physical processes that are operative for lighter versus heavier precipitation events.

Three of the selected regions (central Europe, Siberia, and Canada) experience cold winter climates, and warm-to-cool, moist summers. In the selected regions over Siberia and Europe, many CMIP5 models underestimate precipitation in summer, while overestimating it in winter. In both areas, the MQB values decrease as the choice of quantile threshold increases, suggesting that the model underestimations of summer precipitation are primarily associated with biases in lower quantiles of precipitation. On the contrary, in the selected Canadian region, the CMIP5 models and their ensemble median overestimate summer precipitation. Furthermore, the overall biases of summer precipitation are substantially higher than those of the selected region in Siberia. However, the CMIP5 models exhibit a similar behavior in simulating winter precipitation over the selected cold regions.

Two semi-arid areas (the western United States and Australia) are considered. In both regions, the CMIP5 simulations show high inter-model variability, particularly in summer, while the ensemble median overestimates precipitation in both summer and winter. Here the MQB values of summer and winter precipitation also are similar.

Finally, the CMIP5 models exhibit substantial biases both in summer and winter in the selected southern China region, which is dominated by monsoonal regimes. Further improvements in sub-grid scale convective and cloud microphysical parameterizations are probably necessary to substantially improve precipitation simulations in this region.

The authors stress that the above conclusions are based on an exploratory analysis that exploits some of the available ground-based observations to evaluate the CMIP5 seasonal simulations of continental precipitation. It is acknowledged that the CRU data sets, similar to all other observational data, are also subject to uncertainties that may affect the results. Furthermore, observational biases and uncertainties may have both systematic and random statistical characteristics. Efforts are underway by the authors to decompose the observed biases into systematic and random components using methods introduced by AghaKouchak et al. (2012) to further analyze CMIP5 model uncertainties. It should be obvious that the biases and errors of climate model simulations are not limited to those discussed in this paper. The authors thus advocate that more effort should be devoted to the quantification and characterization of the details of biases exhibited by climate model simulations. It is hoped that further research to develop metrics for evaluating model performance will lead to more reliable precipitation simulations.

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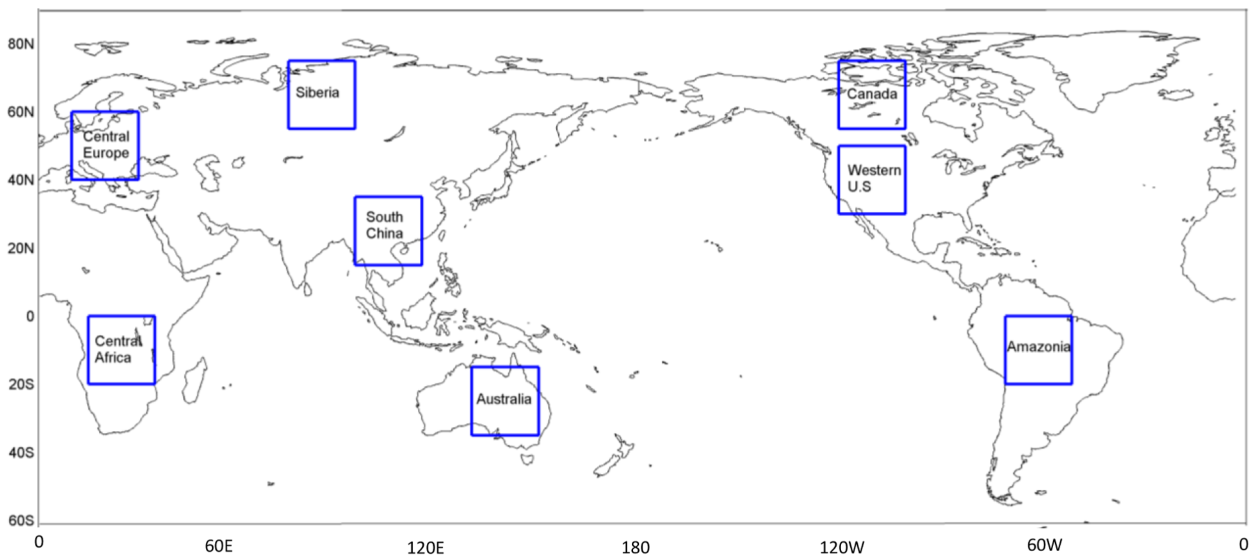

Figure 1: The continental regions selected for this study.

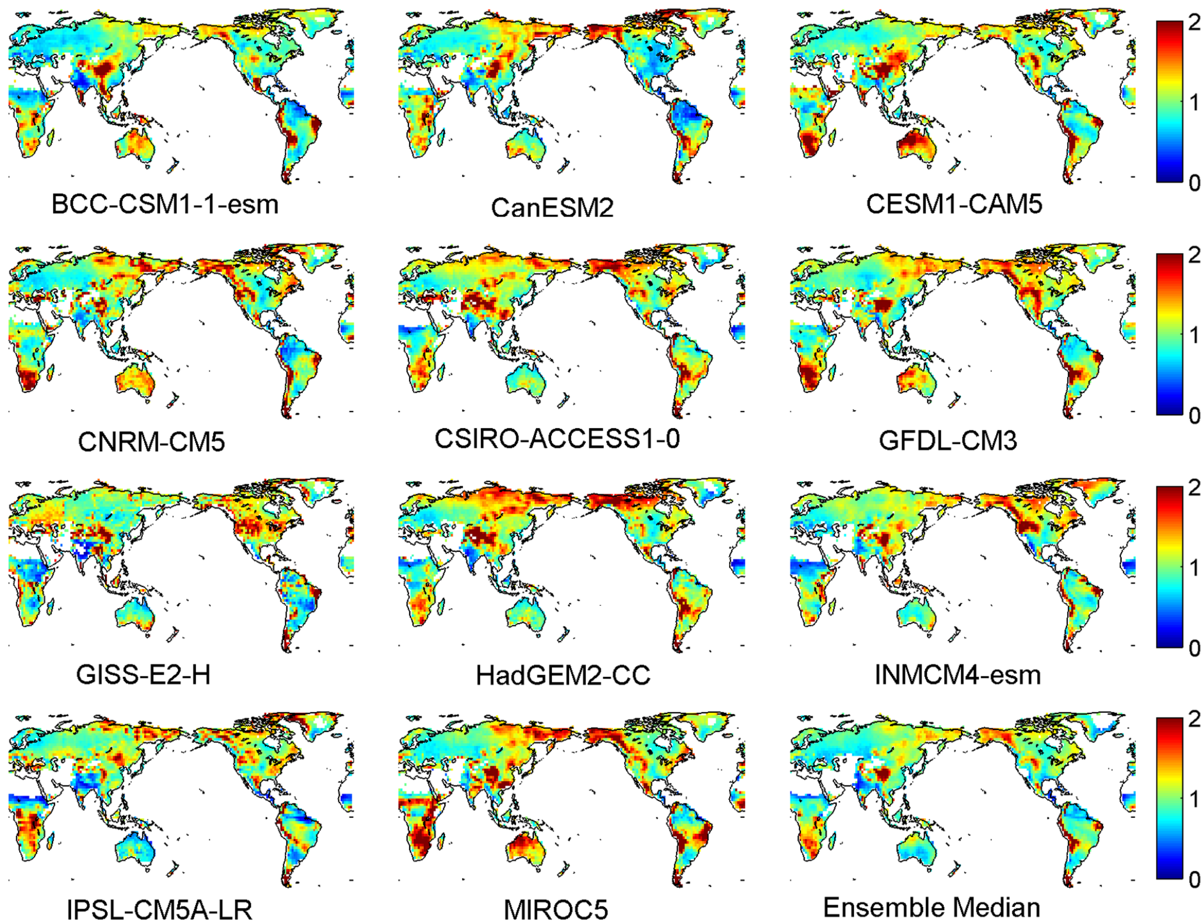

Figure 2: Bias ratio (CMIP5/CRU) of selected climate model simulations of summer precipitation (June, July, August in the Northern Hemisphere, and December, January, February in the Southern Hemisphere).

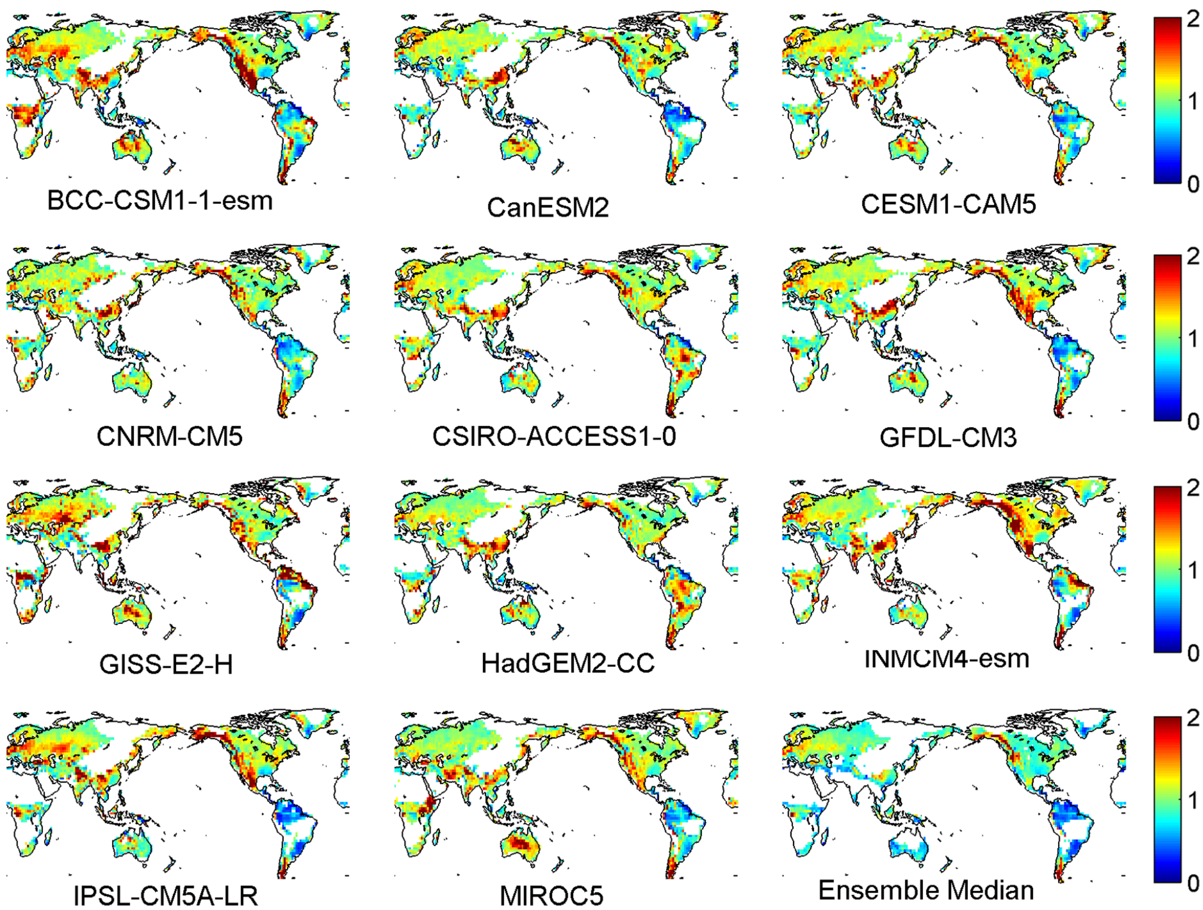

Figure 3: Bias ratio (CMIP5/CRU) of selected climate model simulations of winter precipitation (December, January, February in the Northern Hemisphere, and June, July, August in the Southern Hemisphere).

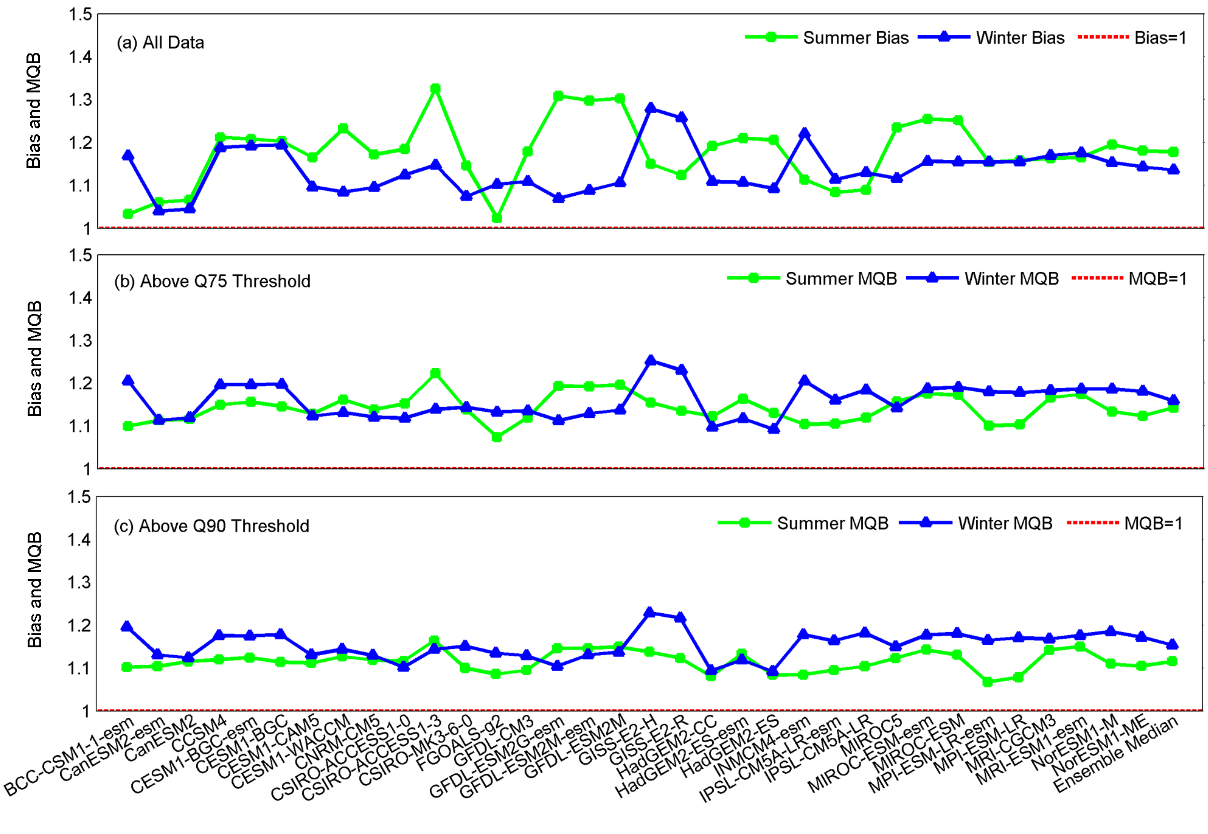

Figure 4: Global averages of the overall bias, MQB above 75th quantile (Q75), and MQB above 90th quantile (Q90) for CMIP5 models and their ensemble median.

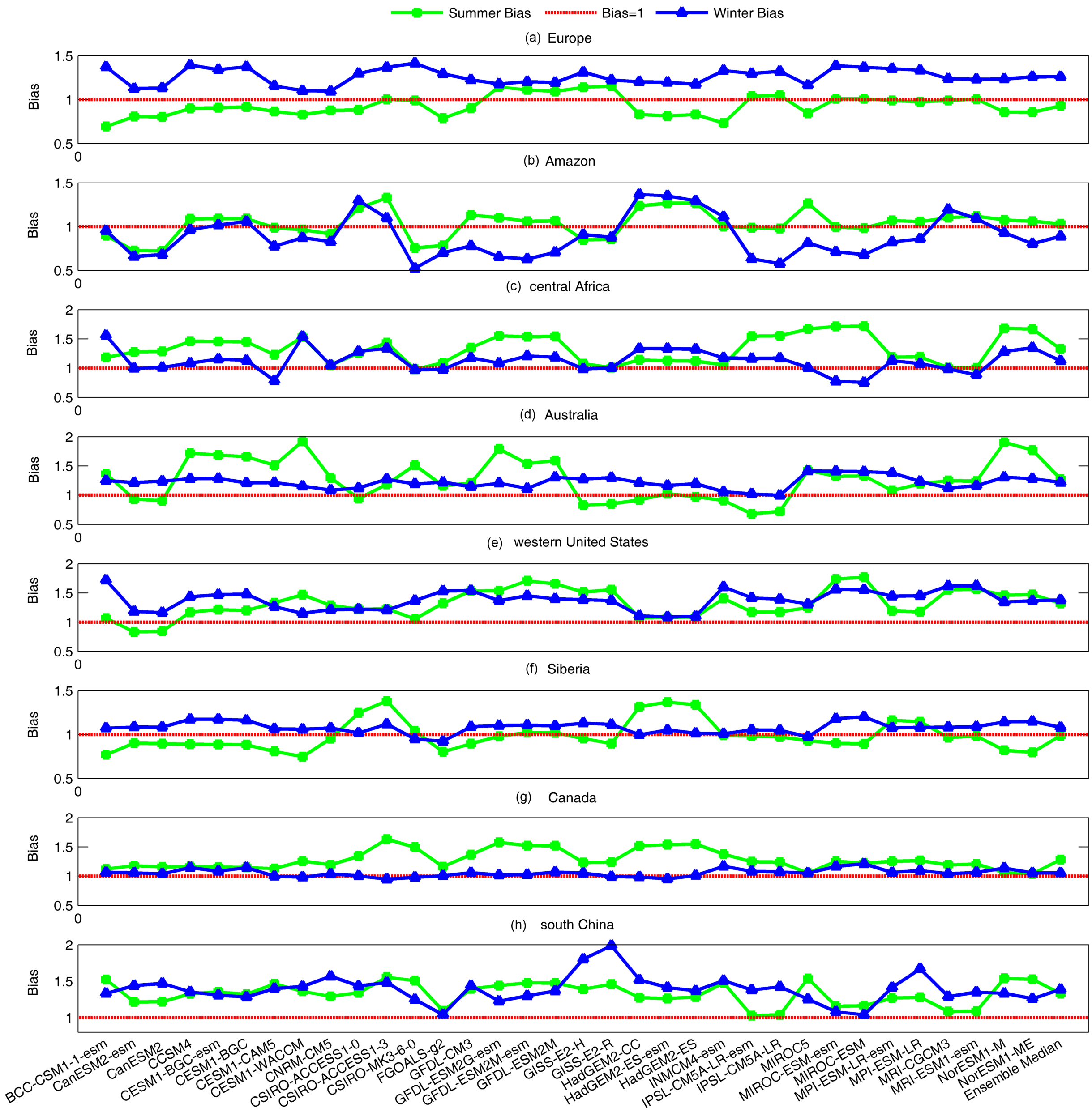

Figure 5: Regional summer and winter biases over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, (h) south China.

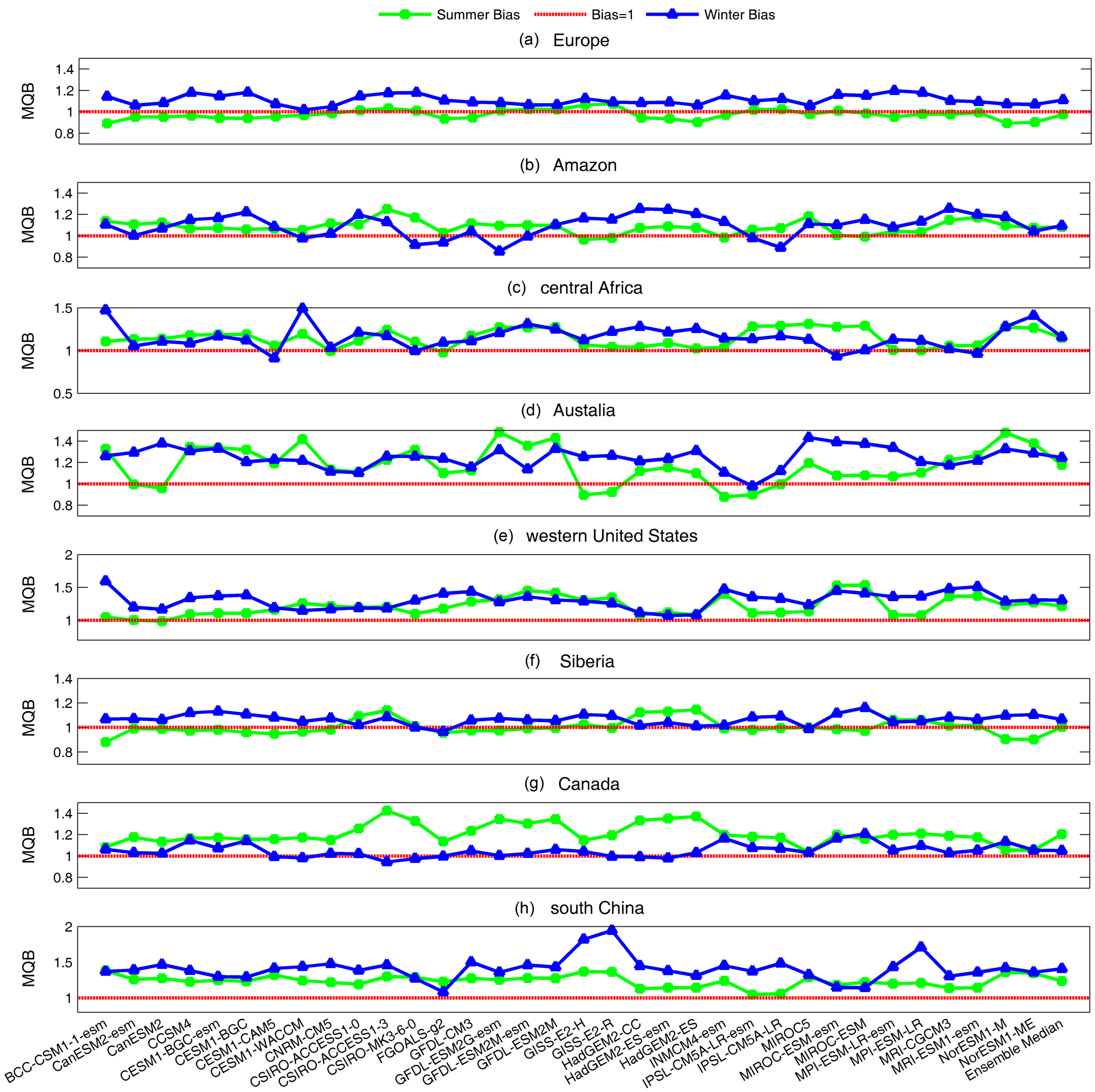

Figure 6: Regional summer and winter monthly quantile bias (MQB, 75th percentile threshold) over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, (h) south China.

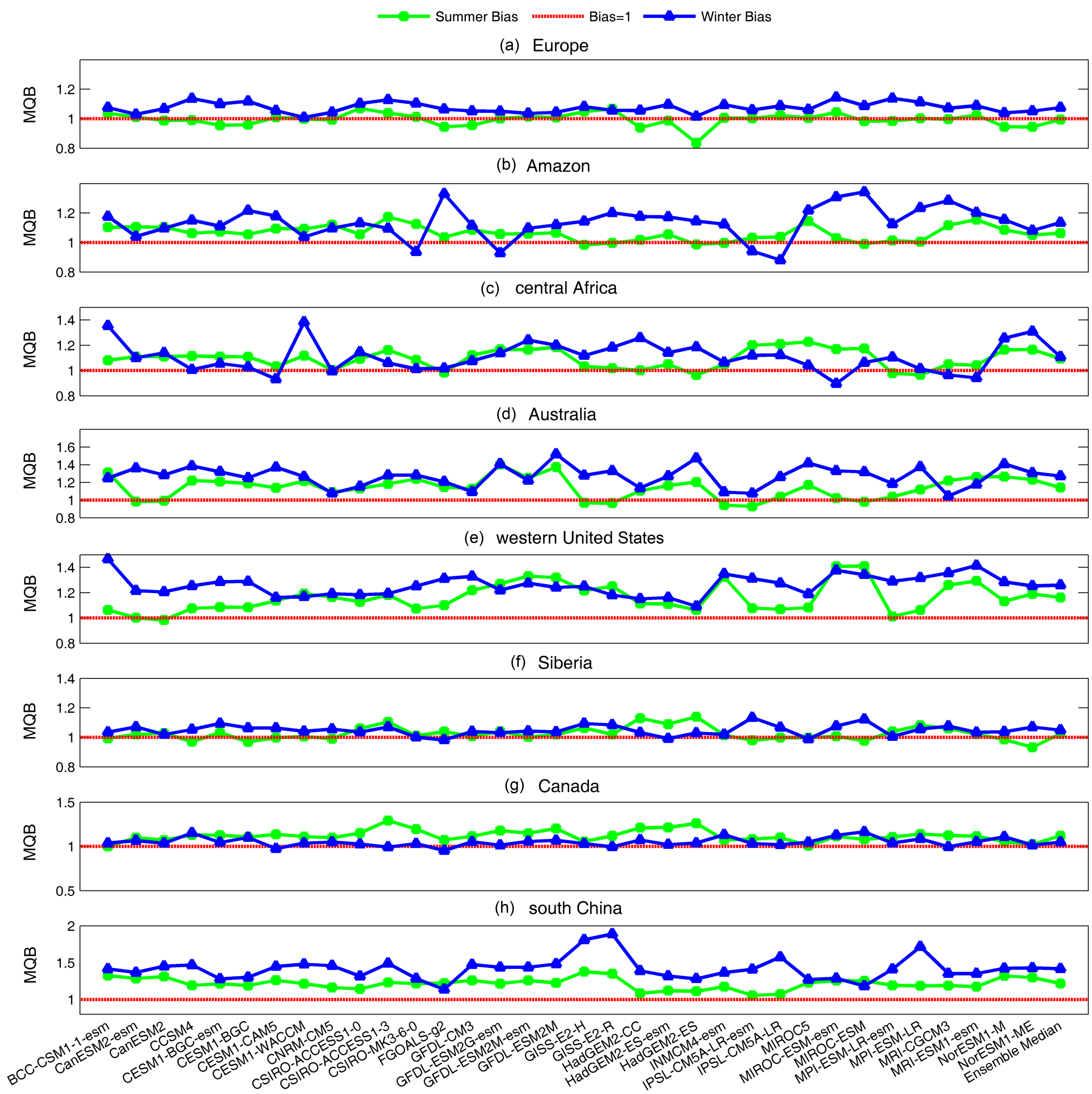

Figure 7: Regional summer and winter monthly quantile bias (MQB, 90th percentile threshold) over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, (h) south China.

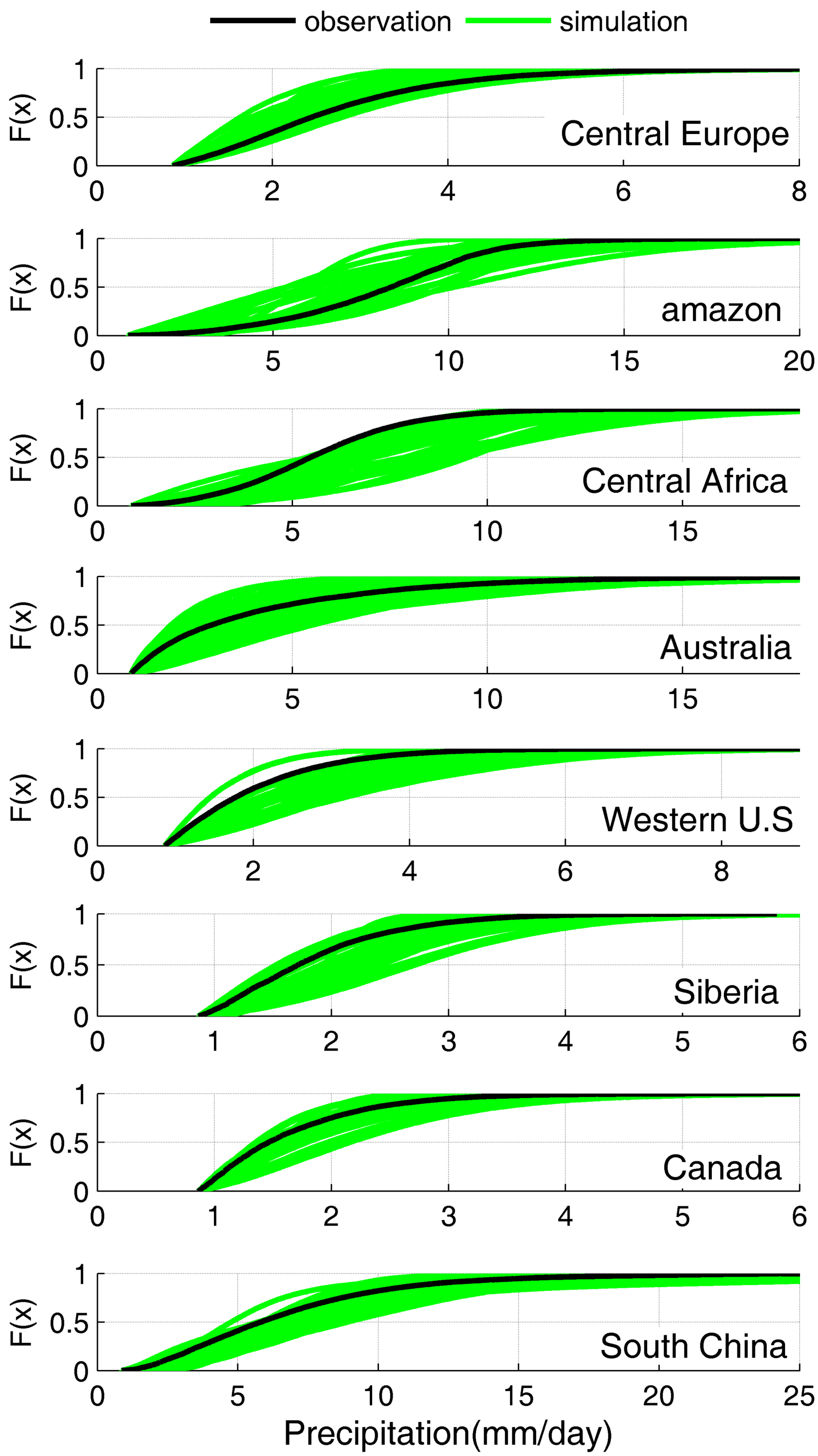

Figure 8: The empirical cumulative distribution functions (CDFs) of the observed (black lines) and CMIP5 precipitation simulations (green lines) in summer.

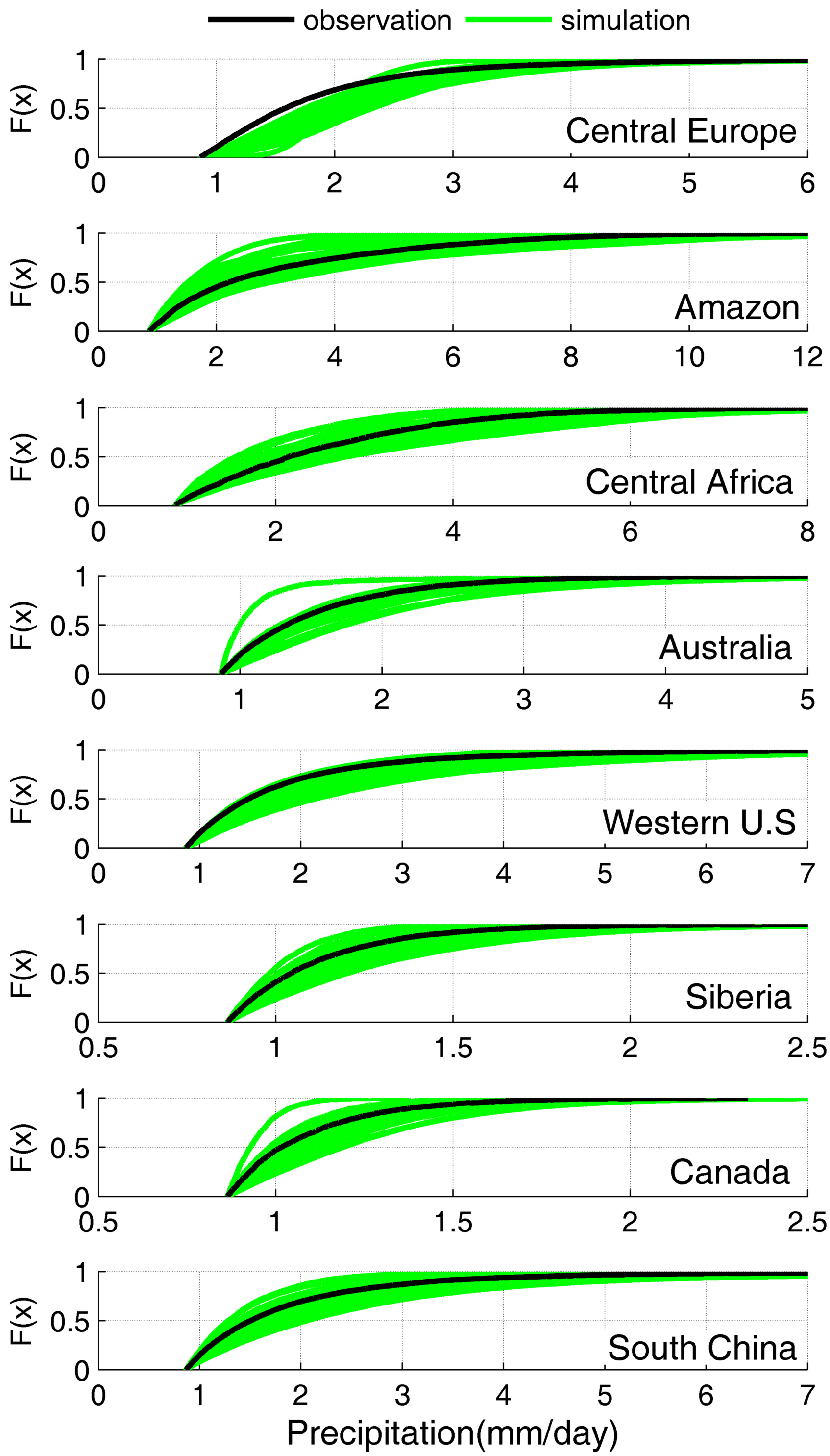

Figure 9: The empirical cumulative distribution functions (CDFs) of the observed (black lines) and CMIP5 precipitation simulations (green lines) in winter.

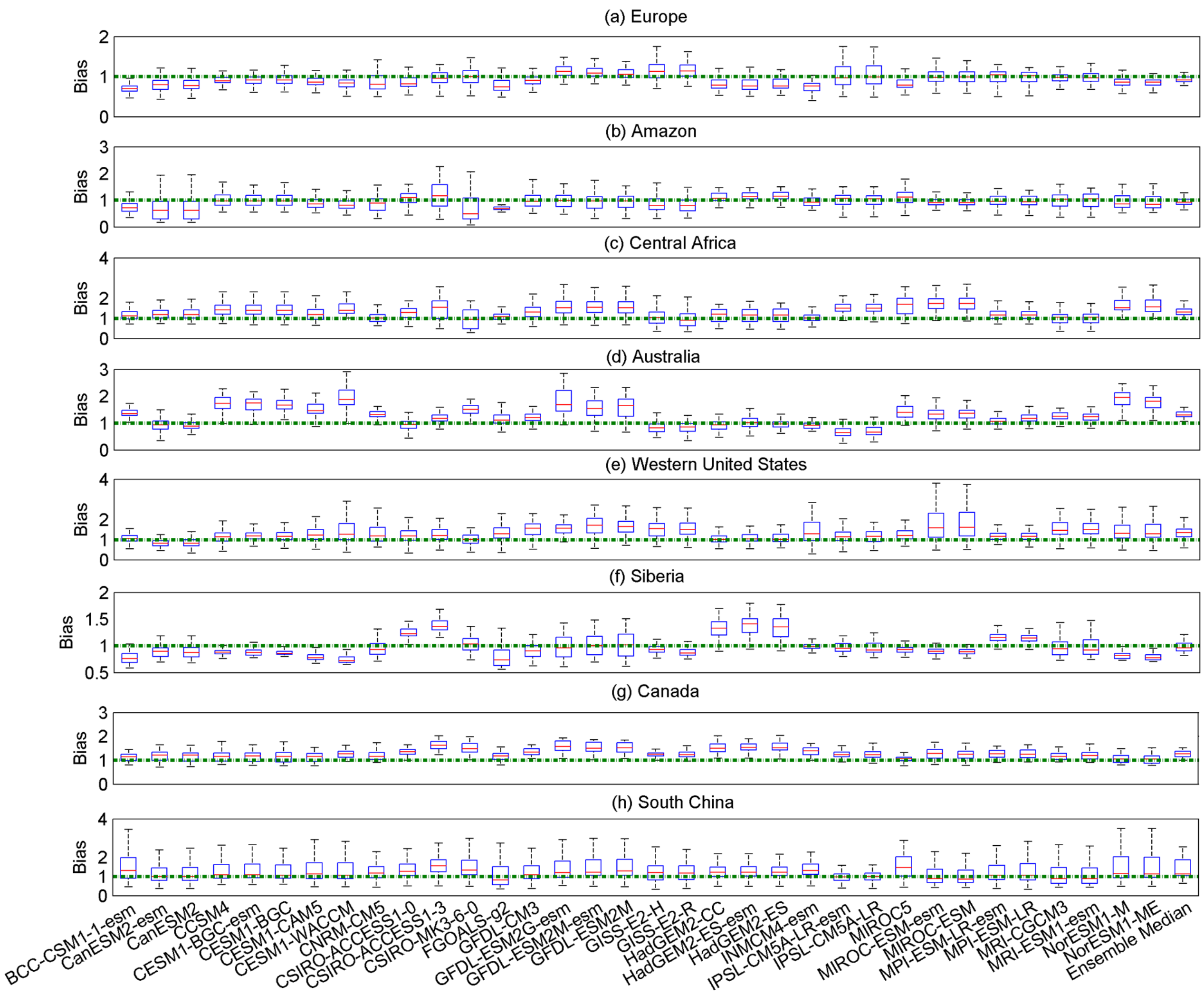

Figure 10: Boxplots of the median (red lines), 25th and 75th percentiles, and whiskers of the biases of each CMIP5 summer precipitation simulation.

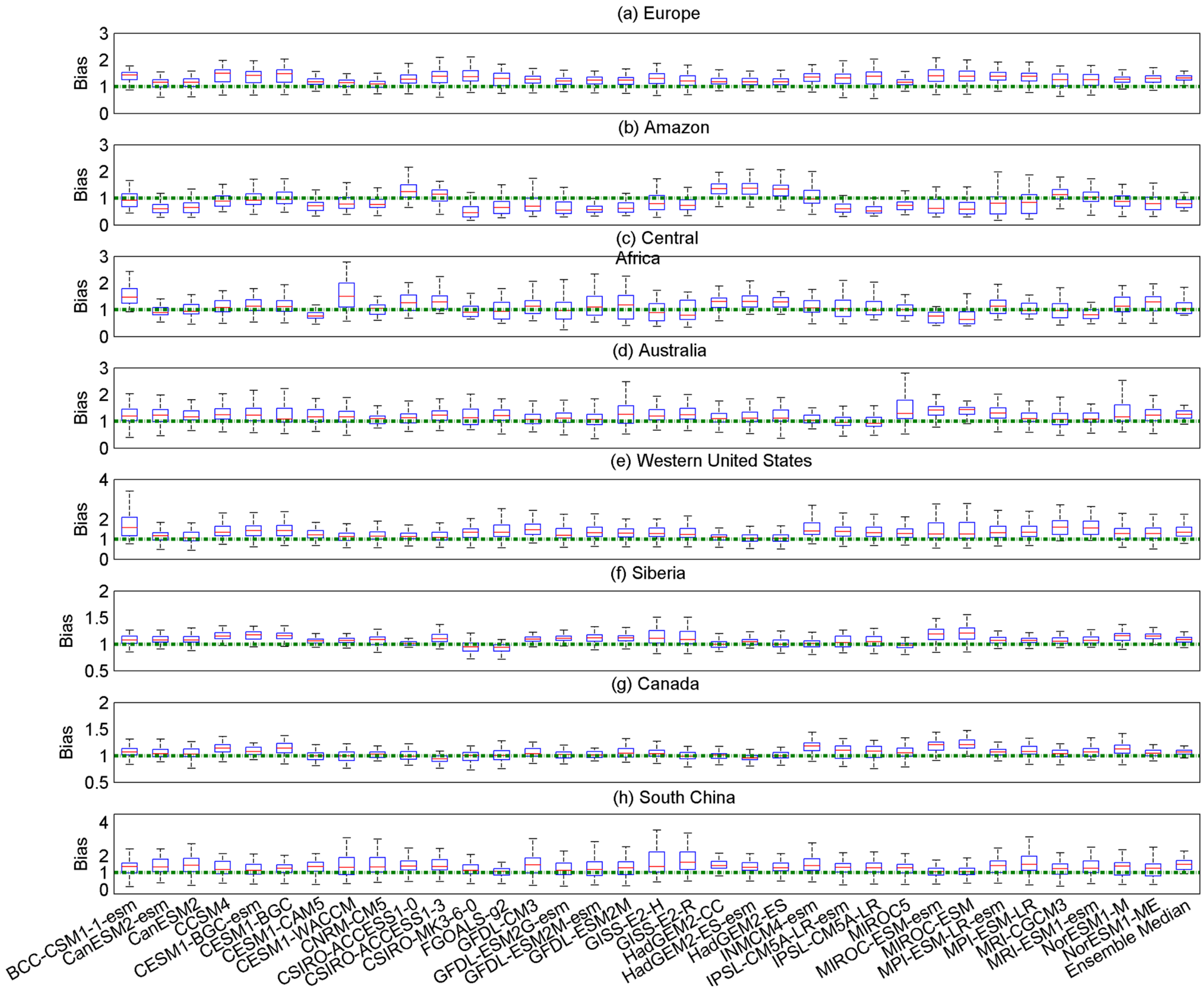

Figure 11: Boxplots of the median (red lines), 25th and 75th percentiles, and whiskers of the biases of each CMIP5 winter precipitation simulation.

Table 1: List of 34 CMIP5 models and their related Institutions and countries (NSF: National Science Foundation; DOE: Department of Energy; NCAR: National Center for Atmospheric Research; CSIRO: Commonwealth Scientific and Industrial Research Organisation; CMA: China Meteorological Administration; CAS: Chinese Academy Of Sciences; TU: Tsinghua University; CERFACS: Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique; JAMSTEC: Japan Agency for Marine-Earth Science and Technology; AOR (UoT): Atmosphere and Ocean Research Institute (The University of Tokyo); NIES: National Institute for Environmental Studies).

Models	**Institution**	**Country**
BCC-CSM1-1_esm	Beijing Climate Center, CMA	China
CanESM2_esm CanESM2	Canadian Centre for Climate Modelling and Analysis	Canada
CCSM4	National Center for Atmospheric Research	USA
CESM1-BGC_esm CESM1-BGC CESM1-CAM5 CESM1-WACCM	NSF, DOE, and NCAR	USA
CNRM-CM5	Centre National de Recherches Meteorologiques	France
CSIRO-ACCESS1-0 CSIRO-ACCESS1-3 CSIRO-MK3-6-0	CSIRO and Bureau of Meteorology	Australia
FGOALS-g2	Institute of Atmospheric Physics, CAS, TU	China
GFDL-CM3 GFDL-ESM2G_esm GFDL-ESM2M_esm GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	USA
GISS-E2-H GISS-E2-R	NASA Goddard Institute for Space Studies	USA
HadGEM2-CC HadGEM2-ES_esm HadGEM2-ES	Met Office Hadley Centre	UK
INMCM4_esm	Institute for Numerical Mathematics	Russia
IPSL-CM5A-LR_esm IPSL-CM5A-LR	Institut Pierre-Simon Laplace	France
MIROC5 MIROC-ESM_esm MIROC-ESM	JAMSTEC, AOR (UoT), NIES	Japan
MPI-ESM-LR_esm MPI-ESM-LR	Max Planck Institute for Meteorology	Germany
MRI-CGCM3 MRI-ESM1_esm	Meteorological Research Institute	Japan
NorESM1-M NorESM1-ME	Norwegian Climate Centre	Norway

Supplementary Material

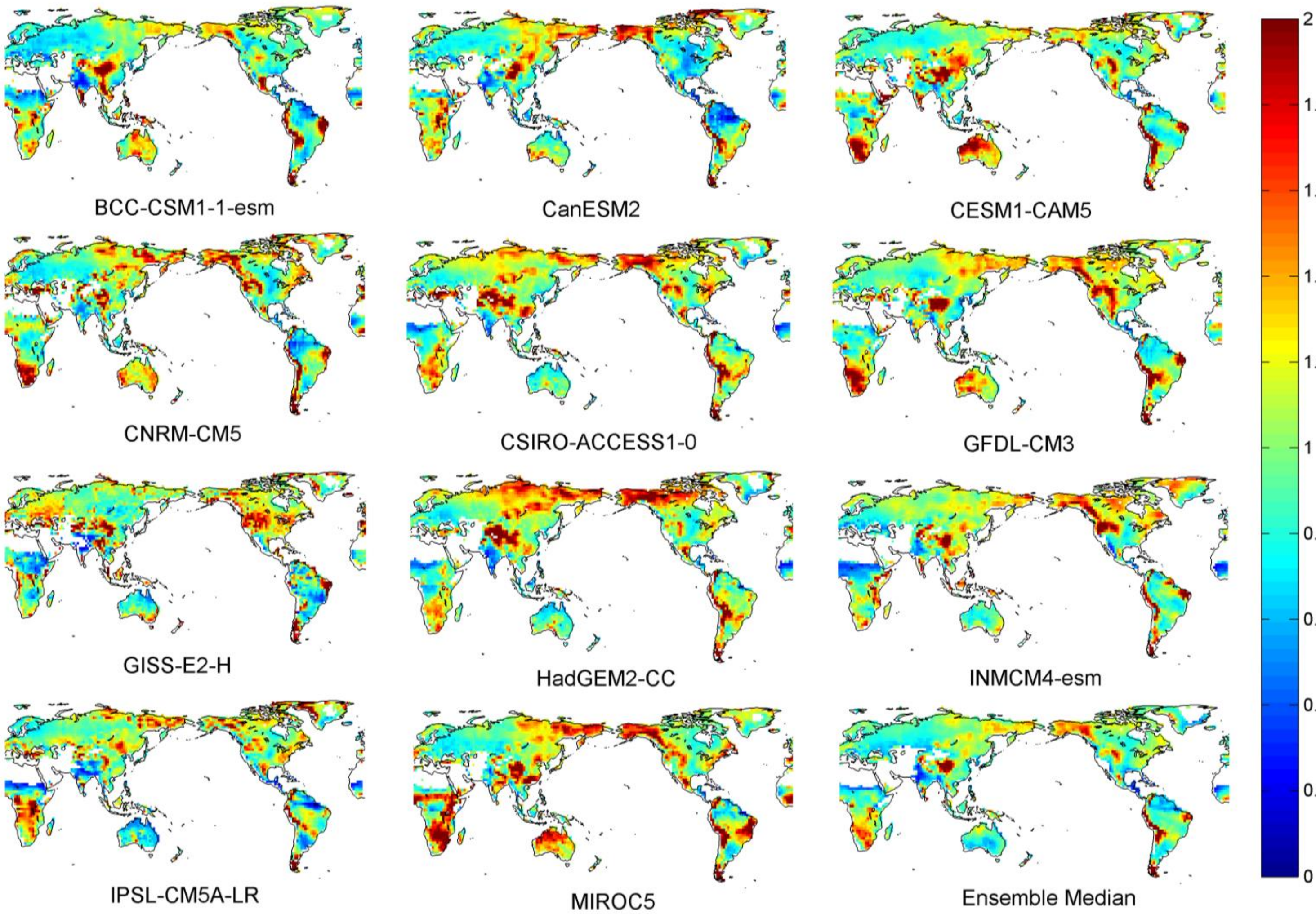

Figure S1: Bias ratio (CMIP5/CRU) of selected climate model simulations of summer precipitation (June, July, August in the Northern Hemisphere, and December, January, February in the Southern Hemisphere) – similar to Figure 2 in Liu et al. (2013), but for the period 1951-2005.

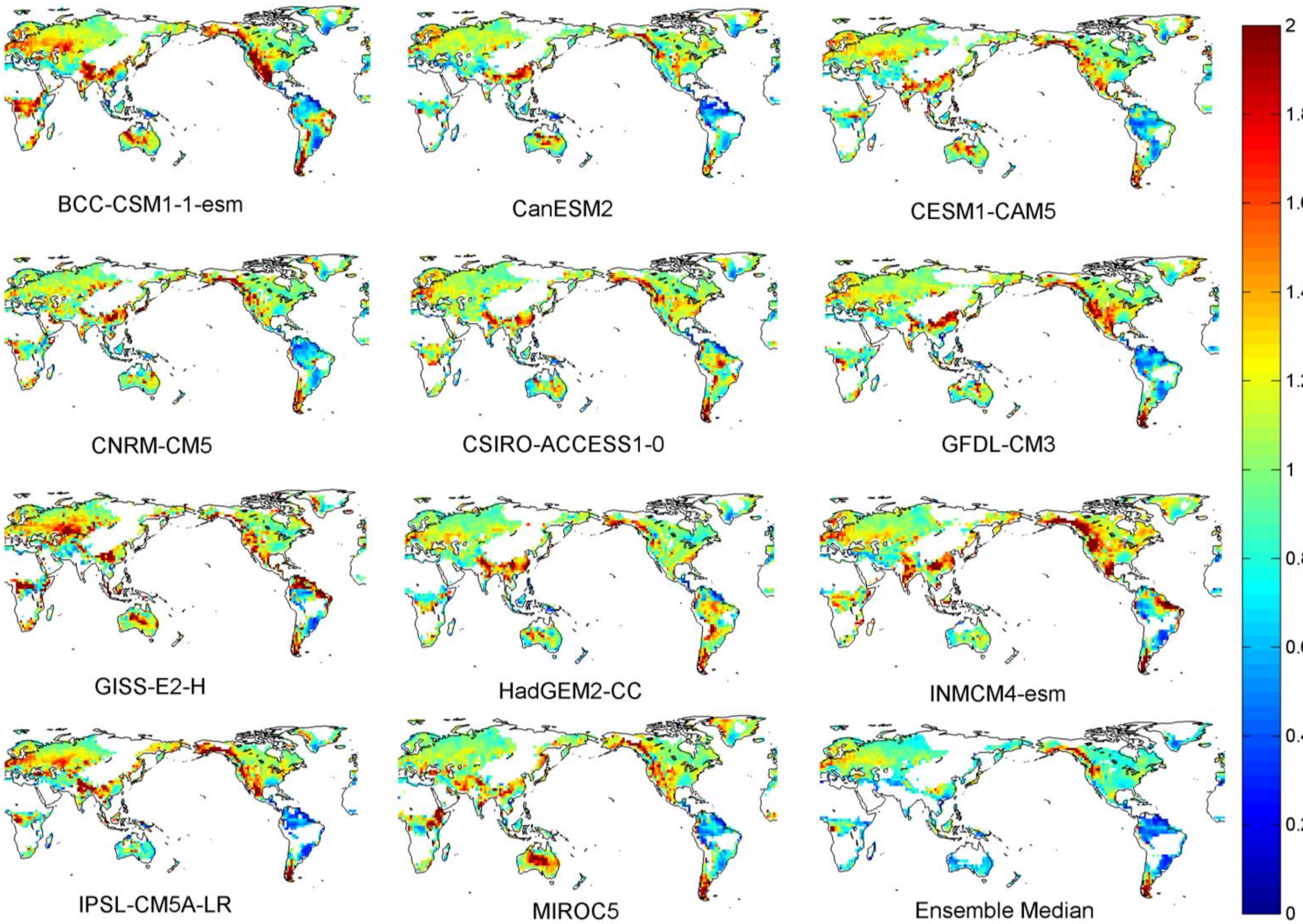

Figure S2: Bias ratio (CMIP5/CRU) of selected climate model simulations of winter precipitation (December, January, February in the Northern Hemisphere, and June, July, August in the Southern Hemisphere) - similar to Figure 3 in Liu et al. (2013), but for the period 1951-2005.

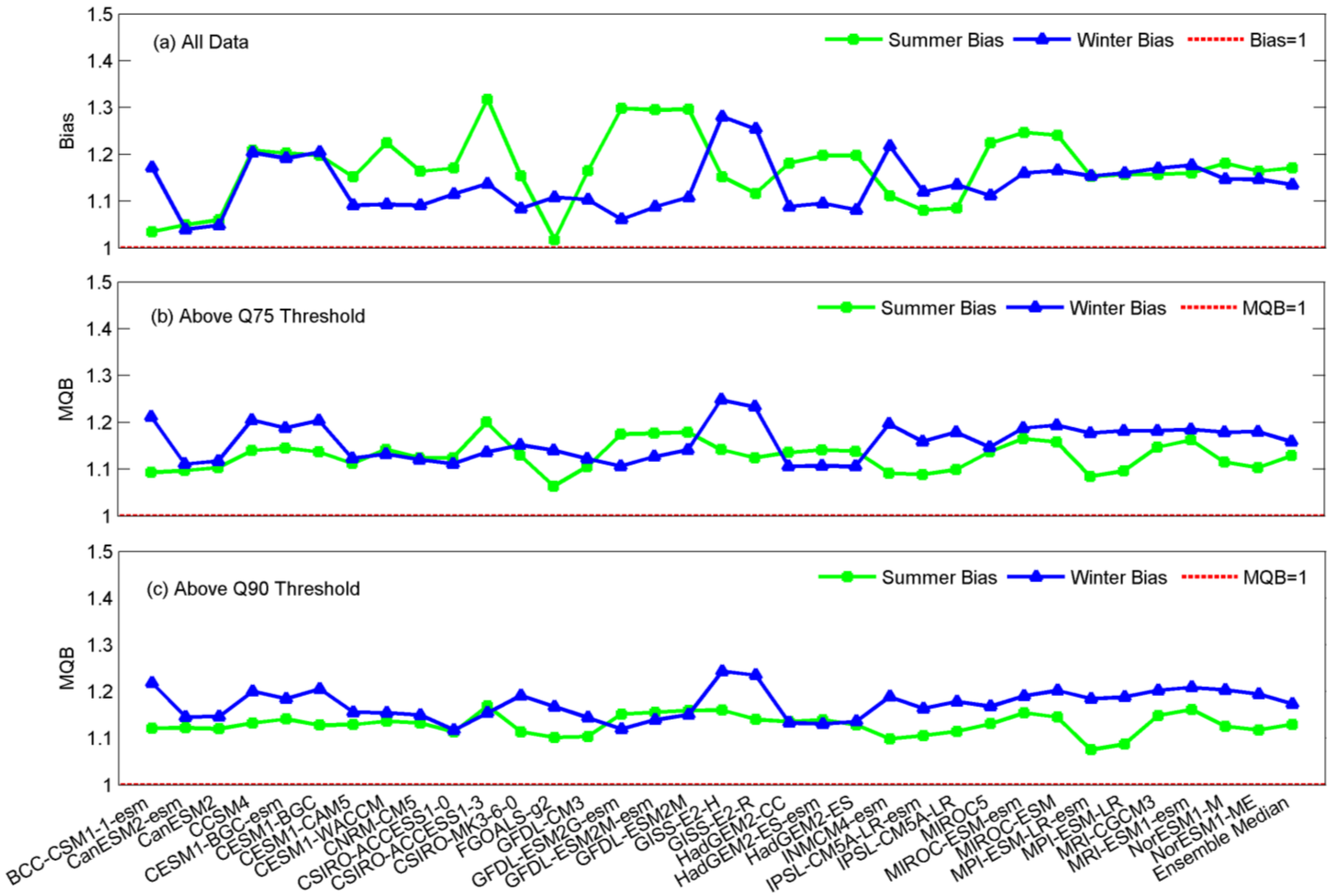

Figure S3: Global averages of the overall bias, MQB above 75th quantile (Q75), and MQB above 90th quantile (Q90) for CMIP5 models and their ensemble median - Similar to Figure 4 in Liu et al. (2013), but for the period 1951-2005.

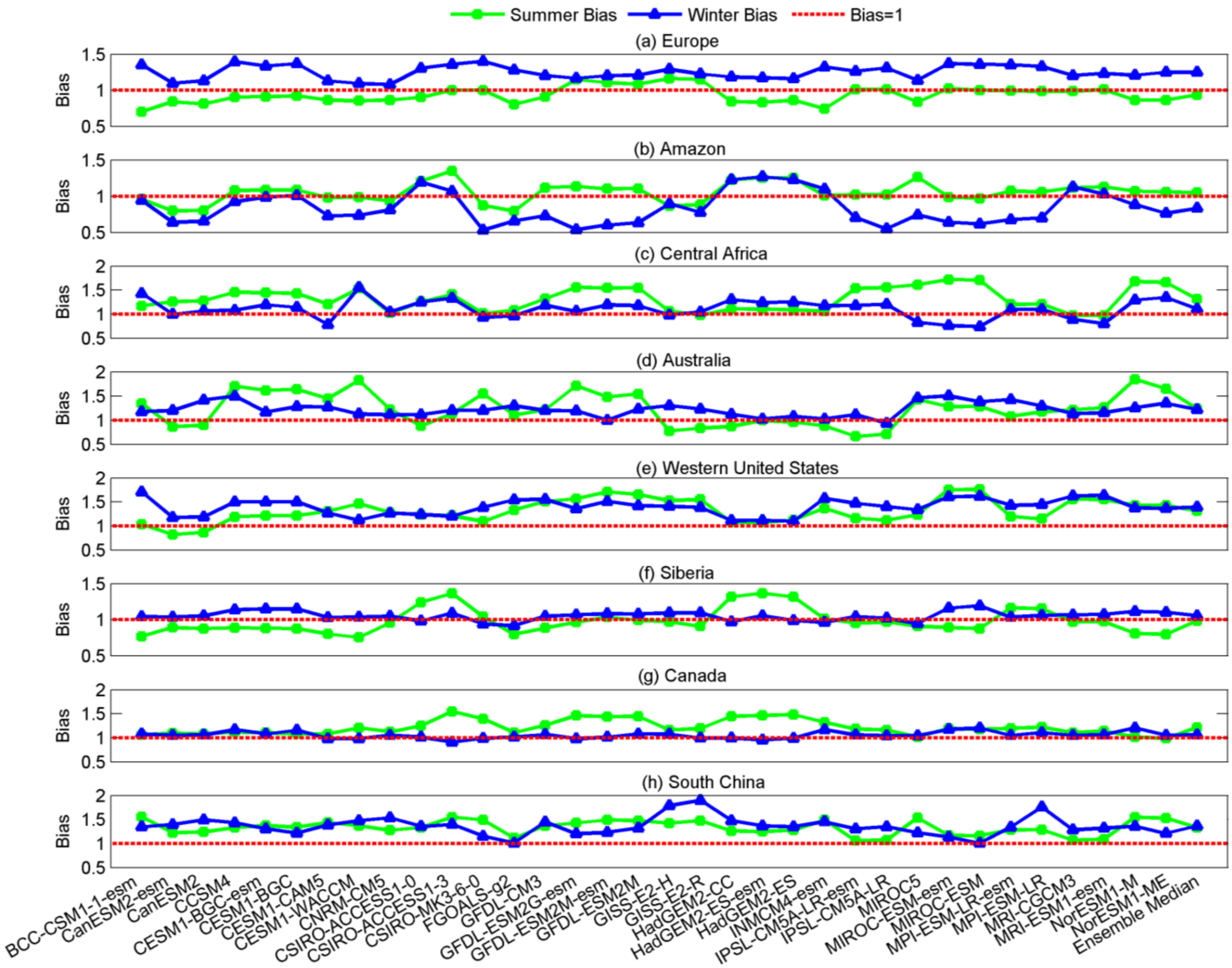

Figure S4: CMIP5 climate model regional summer and winter biases over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, (h) south China - similar to Figure 5 in Liu et al. (2013), but for the period 1951-2005.

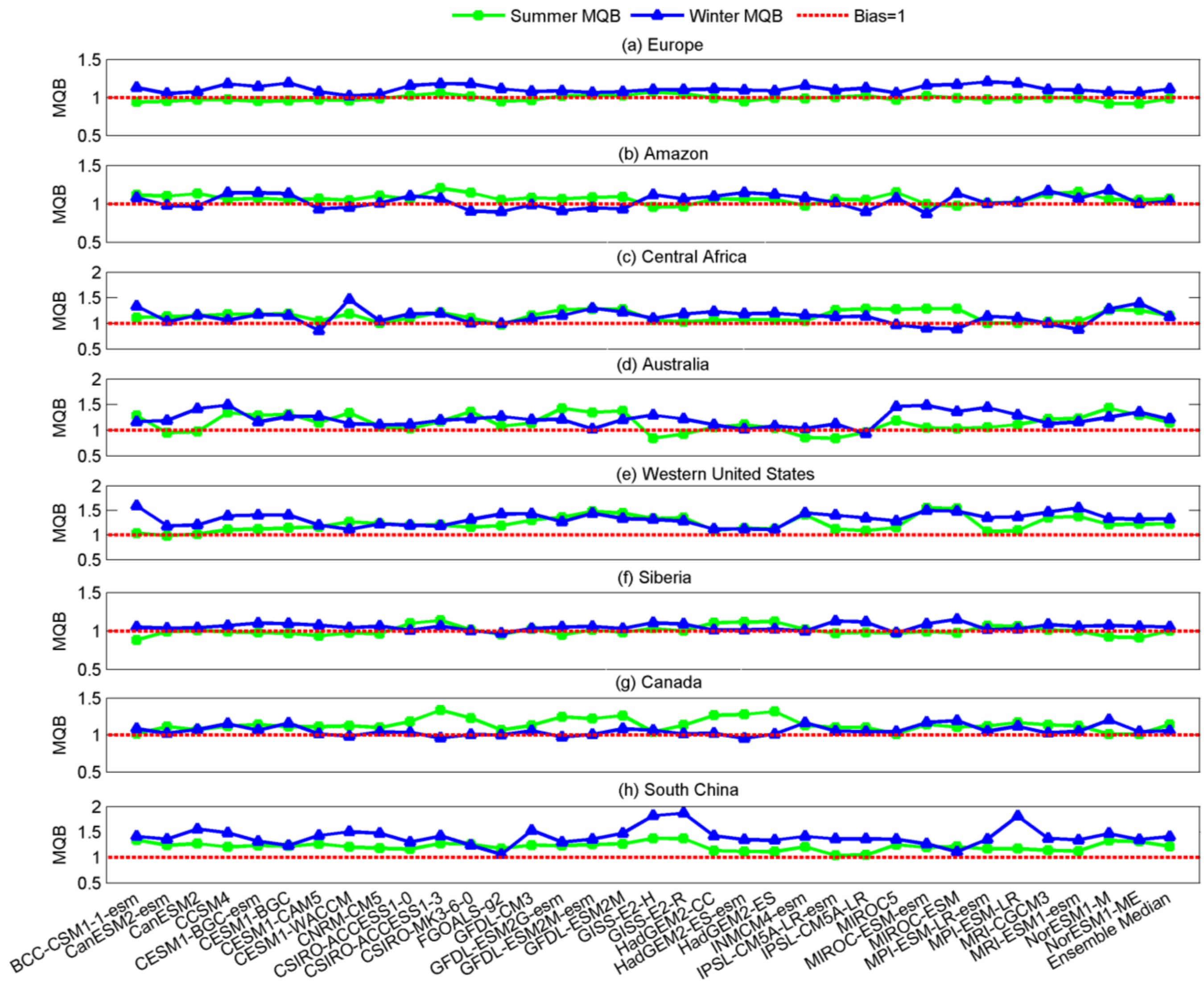

Figure S5: CMIP5 climate model regional summer and winter monthly quantile bias (MQB, 75th percentile threshold) over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, (h) south China - similar to Figure 6 in Liu et al. (2013), but for the period 1951-2005.

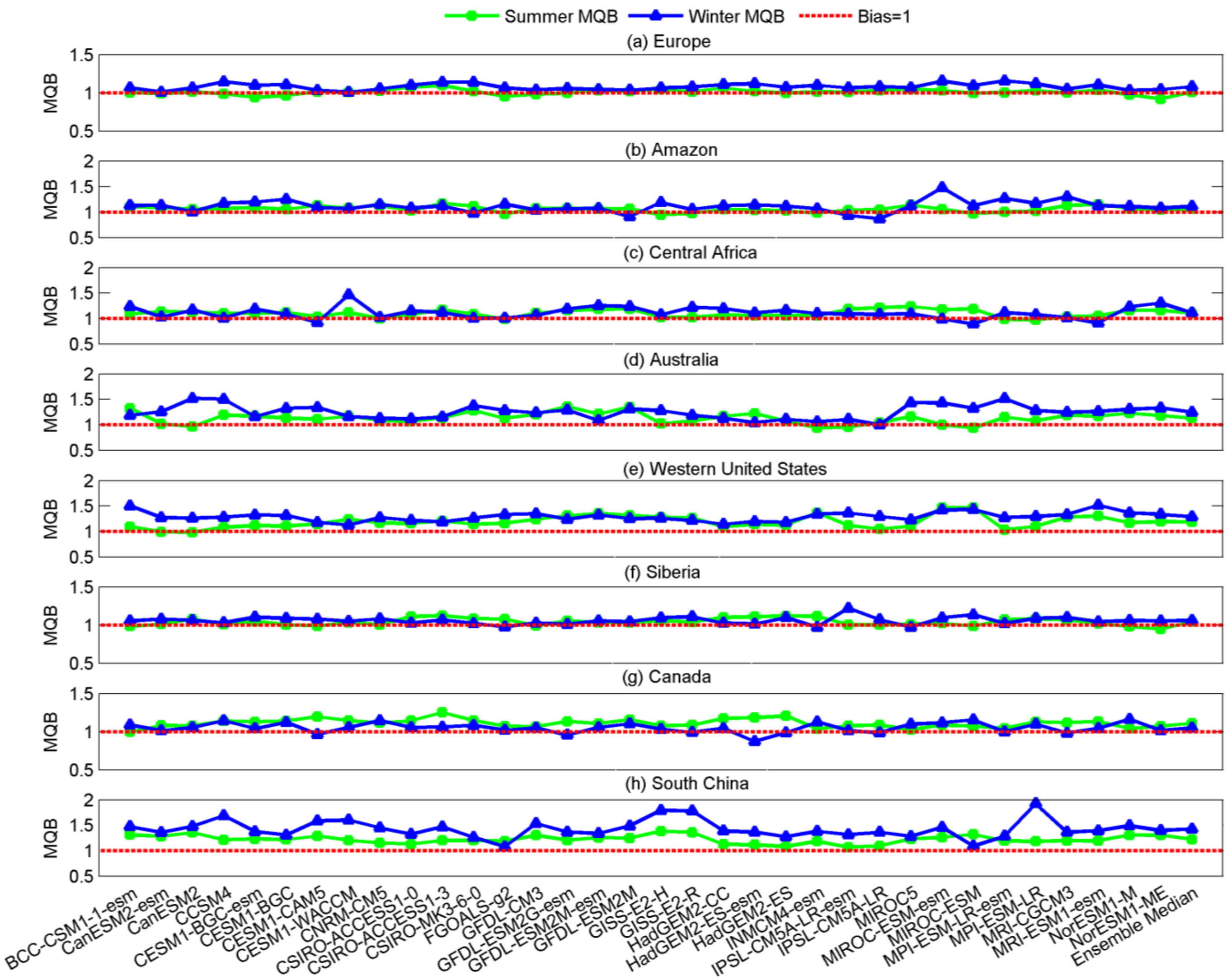

Figure S6: CMIP5 climate model regional summer and winter monthly quantile bias (MQB, 90th percentile threshold) over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, (h) south China - similar to Figure 7 in Liu et al. (2013), but for the period 1951-2005.

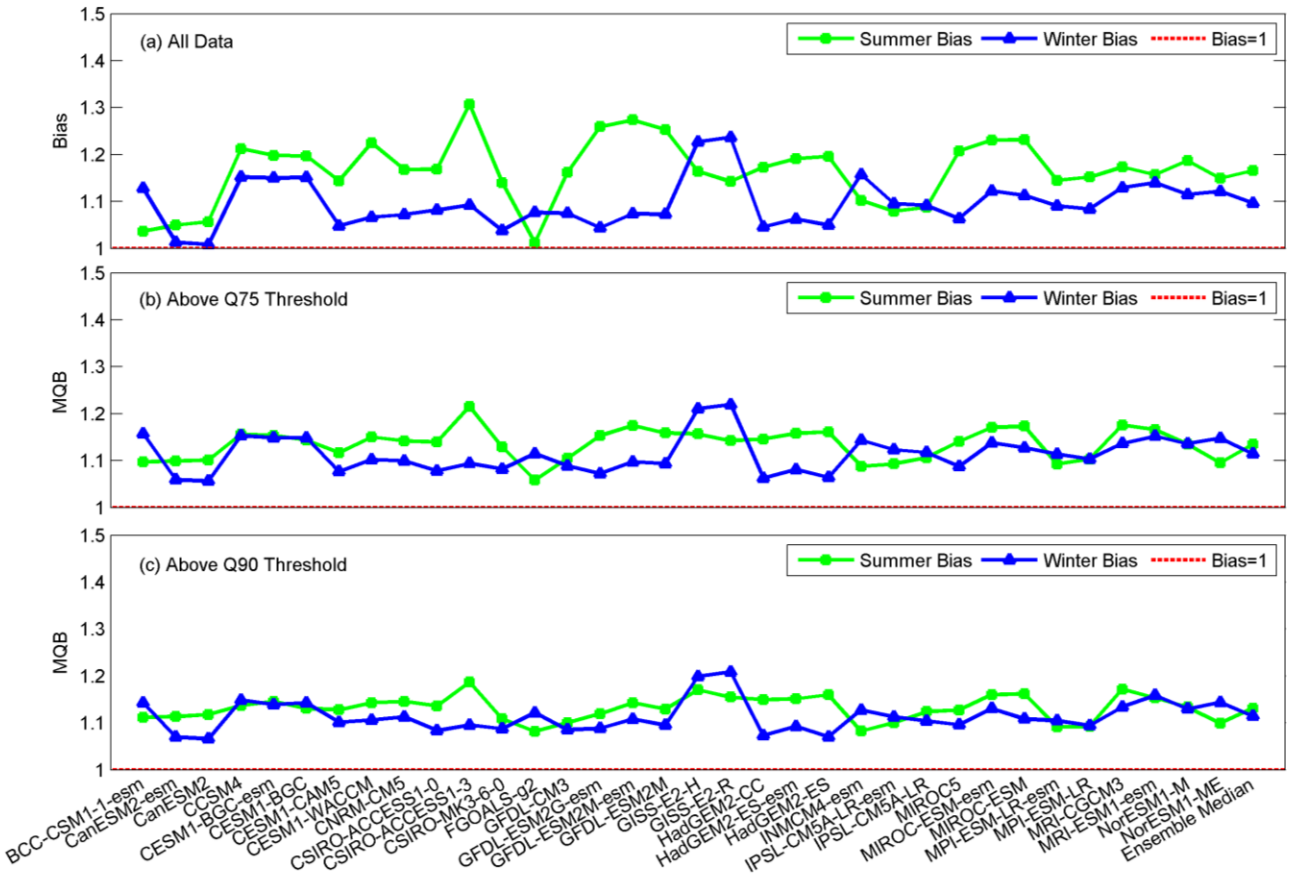

Figure S7: Global averages of the overall bias, MQB above 75th quantile (Q75), and MQB above 90th quantile (Q90) for all the CMIP5 models and their ensemble median relative to the University of Delaware global precipitation data.

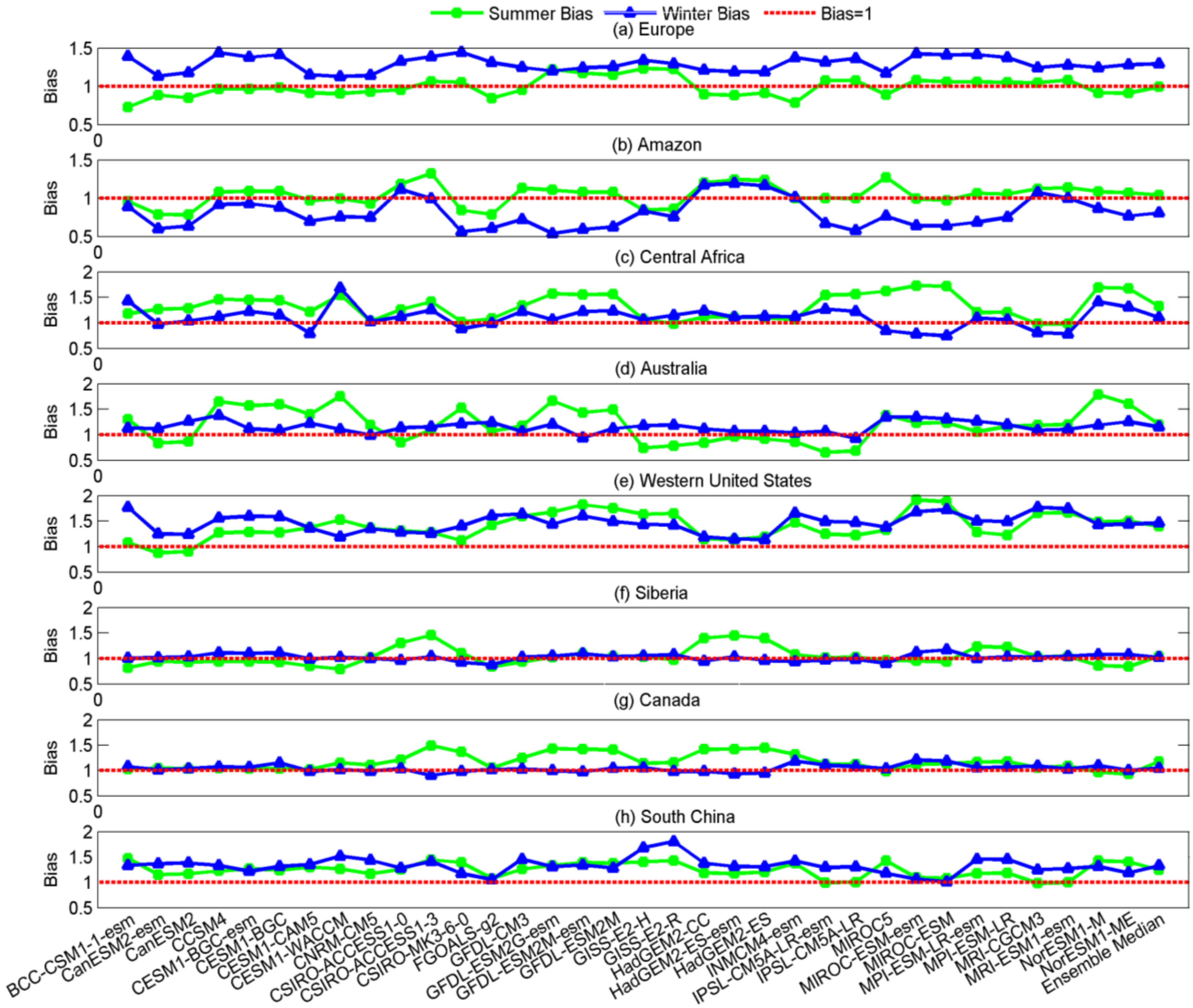

Figure S8: Regional summer and winter relative to the University of Delaware global precipitation data over (a) Europe, (b) Amazon, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, (h) south China.

Reference

Liu Z., Mehran A., Phillips T.J., AghaKouchak A., 2013, Seasonal and regional biases in CMIP5 precipitation simulations, submitted to *Climate Research*.